Developing a Sensor based Homecare System
The Role of Bluetooth Low-Energy in Activity Monitoring

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Abstract: Home healthcare systems have become a focus of research due to the shifting care requirements of the elderly. Malnourishment, independence and activity are becoming vital metrics when monitoring patient illness. Monitoring devices described in research however express issues in the consistent remote capture of these metrics. This work presents the role of Bluetooth Low-Energy Beacons (BLE) in community based healthcare by examining how passive activity monitoring can assist patients coping with independence and disease management within their homes as an indoor Proximity System (IPS). BLE sensors will be placed on the patient, in their home and on objects of interest (OOI) such as water bottles, kettles and microwaves. Research described in this paper will focus on accuracy of BLE beacon as an IPS for lifestyle monitoring and its application to intelligent healthcare. This is achieved by creating a model of patient care requirements structured using activities of daily living (ADL) which is evaluated using patient activity pattern recognition in captured sensor data. Pattern analysis uses the changing distance values between BLE sensors to determine movement motion and location which contribute to the activity, sensor based care model. Results support efficacy when using BLE beacons as an IPS with patient activity patterns becoming observable through monitoring with a consistent ability to distinguish interactions in activity patterns capture. Future experiments will focus on analysis captured sensor metrics to determine care outcomes.

1 INTRODUCTION

National healthcare systems have been placed under strain with hospitals nearing capacity and staff shortages threating to affect the quality of care provided. Research has often focused on technology as a method to deliver more efficient processes. With over 65s accounting for more than 60% of hospital emissions (Office for National Statistics, 2012), healthcare prioritises treating elderly patients at home rather than having them cared for at hospitals. Community nurses which operate as home care givers are in decline however, by 2025 due to high demand and diminishing numbers the profession may no longer exist (CarersUK, 2015). Independent care givers often fill the gap left by declining community nurses with CareUK estimating one in eight people provide informal care for a relative, friend or neighbour where professional nurses are not available (CarersUK Policy Briefing, 2015). The diseases elderly patients suffer from have changed drastically with improving living conditions and access to modern medicines. Infectious diseases such as measles, whooping cough and scarlet fever which would require hospital treatment have been declining worldwide (Armstrong, G. L., 1999). Non-communicable diseases (NCDs) have been on the rise however, conditions such as stroke, cancer, heart disease which are not infectious now account for 68% of total deaths worldwide (WHO, 2012) and present unique challenges for home based care (Dye, 2014).

NCDs such as Dementia, a degrative neurological condition (DNC) are now the leading cause of death (Office for National Statistics, 2016) in England and Wales, with the elderly population of 65 and over four times more likely than other age groups to suffer from a NCD (Office for National Statistics, 2016), this makes this age group the focus of NCD and DNC care research outcomes and a potential avenue for reducing healthcare system strain through home monitoring. Healthcare research has identified lifestyle, activity, nutrition and independence as key factors in the progression and management of NCDs for elderly patients (Katz, 1983). Current research describes devices which can remotely monitor patients and has successfully shown

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efficacy in delivering remote care. This paper will describe the reasoning for exploring BLE (Bluetooth Low-Energy) for IPS (Indoor Proximity System) as an application of Intelligent Healthcare.

2 INTELLIGENT HEALTHCARE

Intelligent Healthcare aims to examine methods of caring for patients in their homes while maintaining acceptable standards which a community nurse could provide, using technology. A substantial amount of the research in this area place within a smart home or health smart home, the augmentation of the home environment to accommodate technology which will benefit the occupant through remote monitoring. Various technologies work to keep a patient or elderly person safe in their home and keep them from being readmitted to hospital. Research areas such as telehealth and telecare look to alert care givers and other care stakeholders to potential events taking place inside the home which may require their attention such as fall detectors, changes sedentary levels and possible malnourishment (Stowe, S., & Harding, S., 2010). Research within intelligent healthcare has substantiated the efficacy of remote caring technologies for NCDs such as heart disease and diabetes through increased monitoring in the home (Allard et al., 2014).

2.1 Remote Patient Monitoring

Remote Patient Monitoring (RPM) is an effective method for providing intelligent healthcare remotely to patients suffering from NCDs such as Chronic Heart Failure (CHF), Chronic obstructive pulmonary disease (COPD) and diabetes. Nakamura et al has demonstrated the efficacy of this method of remote, technology assisted care by examining the effectiveness of RPM in reducing the risk of mortality for CHF patients compared to 'usual care' (Nakamura et al, 2013. A significant factor in reducing mortality when using RPM has been the higher frequency of measurements from the patient as this allows for a greater amount of data to be examined and thus an intervention made timelier. Measurements taken with RPM devices may include bodyweight, blood pressure and heart rate. During Nakamura et al experiments, patients with medication management via RPM could have their medication dosage managed accurately from the more frequent data captures thus reducing the likelihood of mortality by CHF. RPM appears to be an effaceable approach to delivering intelligent healthcare, by capturing data reportedly and analysing it using medical models it can be possible to predict, prevent and manage illness without the need of hospital or nurse visits to collect this data. Clinical effectiveness of patients submitting frequent clinical measurements from the home environment to allow a greater spectrum of data points (Nakamura et al, 2013) is a clear factor in the success of the technology and the patients outcomes.

However, NCDs often have a wider variety of care requirements, where CHF can be measured remotely using a simple heart or pulse monitor, NCDs have a wide variety of ailments and symptoms associated with their acceleration. Factors such as loss of independence, inability to perform motions, deviations from normal tasks over time and dehydration at home. Research has attempted to capture this data and use RPM technique to remotely provide visibility to these symptom changes over time with varied success. As such, RPM forms a significant basis for the underlying research presented in this paper as the mechanism of using multiple data points in activity monitoring evaluation with a focus on selecting and testing devices which may accurately capture the required data.

2.2 Activity Monitoring

Patient activities are a key determinant when assessing independent living for elderly patients. Chiauzzi et al described activity monitoring as "sensors which monitor patient's domestic routines and daily activities such as movement around the house, bed and chair occupancy, the opening of cupboards, doors, fridges and wardrobes, and use of electrical devices such as kettles, TVs and lamps" (Chiauzzi et al., 2015). Factors which can affect the development of a NCD in the elderly are measured using the Activities of Daily Living (ADL), a set of standards by which professional caregivers observe and assess patients care outcomes. Activity monitoring for ADL uses passive sensors recording the domestic environment and patient interactions there within. Data captured using monitoring is observed for patterns and the recognition of significant deviations from what is expected under ADL guidelines which guide care efforts, provide timely interventions and assist in future diagnosis.

2.2.1 Devices for Activity Monitoring

Devices which employ sensors to be used in activity monitoring vary greatly in operation and accuracy. Consumer wearable devices for activity tracking have shown promise in post-surgery recovery in cardiac patients, pulmonary rehabilitation, and activity counselling in diabetic patients, among others (Chiauzzi et al., 2015). Research however, has described several limitations when using intelligent healthcare focused activity monitoring to obtain the data required for ADL analysis. Nangalia et al describe how sensors such as occupancy and door sensors, which are used to determine sedentary levels, have deficiencies which reduce accuracy or become limited when used in homes with multiple occupants (Nangalia et al., 2010) and therefore can't be relied upon for RPM of activity. Positioning sensors also have natural barriers with line of sight (LOS), passive infrared (PIR) sensors which monitor patients, rely on microwave emissions to detect motion which can be intercepted by walls, objects or additional occupants (Barlow et al., 2007).

2.3 Indoor Proximity Systems

Indoor Proximity Systems (IPS) use sensors to approximate position within a structure. Proximity sensors capture locational data by broadcasting an advertisement radio wave which is intercepted by a receiver located on a person (Feil, 2016). The distance between the sensor which emits the wave and the receiver is calculated using received signal strength indication (RSSI). As radio wave accuracy is highly dependent on environment the RSSI is used to interpret distance from an advertising sensor and thus location is estimated based on proximity. Environments using proximity for activity monitoring have several advantages over currently implemented remote activity monitoring devices. Radio wave advertising can pass through solid objects, eliminating the issue of requiring LOS (Kyoung Nam Ha et al., 2016). Radio waves could determine intention and movement through increasing or decreasing proximity from a sensor to the receiving device as illustrated in figure 1. As RSSI grows stronger between a sensor and a receiver, locality, motion, intention and proximity can be determined (Kim et al., 2015). Among the challenges of using proximity for Activity RPM is the use of RSSI. Multiple advertisement points could increase approximation within a home but the efficacy of this is largely untested in that environmental context. Multiple advertisement points could increase approximation within a home but the efficacy of this is largely untested in that environmental context. As such this paper will outline experiments to increase accuracy and ultimately form pattern recognition of patient activity using IPS.

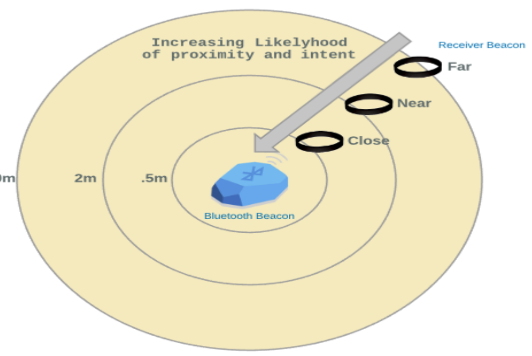

Figure 1: Proximity ranges from emitter to approaching receiver.

2.3.1 Bluetooth Beacon IPS

Bluetooth Low-energy was chosen as the device to be incorporated into a potential IPS for activity monitoring. Developed as Bluetooth version 4.0 and primarily designed to reduce the power consumption, BLE is a universally recognised standard of radio signal, interpretable by any number of devices within the last 15 years. Able to fit onto small circuit boards and operate up to 2 years before exhausting its battery. The potential for use in intelligent healthcare is wide in scope due to the interoperability with devices, low cost and low power output (Feil, 2016). As with all proximity based devices BLE beacons broadcast an RSSI to understand and capture approximate locations of receivers in its range.

2.3.2 Recognising Patterns in IPS Data

Using BLE as a remote IPS to gather activity patterns of elderly patients requires the implementation of a standard of observation with efficacy in homecare environments such as the activities of daily living (ADL) (Katz, 1983). Interactions captured should align with ADL conditions for independence and health as table 1 outlines.

Table 1: ADL By Room or Item Interaction.

ADL Condition	Room or Item Indication
Sedentary Levels	Movement through proximity ranges
Eating	Immediate Proximity to Fridge, Microwave, Oven
Drinking	Manipulation and Proximity to BLE Water Bottle
Toileting/Bathing	Near Proximity to Bath
Motion/Transferring	Movement between Proximity Beacons over time

By placing BLE beacons throughout patient's homes, various rooms of the home will emit proximity radius. A patient wearing a receiver would move between, stay sedentary or interact with objects in these radii. This research proposes it may be possible to capture and align these activity events to ADL conditions to remotely determine lifestyle factors which may affect a patients NCD. Figure 2 below, illustrates possible configuration of proximity ranges to determine ADL conditions as described in table 1. An occupant with a receiver would invariably be in range of several beacons organised and identified by their rooms or objects. The strongest signal strength to the receiver worn by the patient will reveal the occupant's location at any given time while showing intention through the movements between ranges of BLE.

Figure 2: BLE Beacons: Room placement in fictional environment.

This method of monitoring has gained efficacy through research such as by Zhao et al., applying proximity zones by room to an experimental workplace employee activity they observed individuals could be tracked with current occupation approximated, i.e. taking a break or working at their desk (Zhao et al., 2014). This research has also conducted experiments to determine the best method of IPS placement. The focus of experiments in the work reported here however will rest with distinguishing ADL interactions in proximity zones, captured and extracting patterns from data which fits into a predictive healthcare algorithm to determine ADL conditions.

3 EXPERIMENTS

Experiments conducted in this paper form an iterative process of implementing and testing the efficacy of BLE beacons for intelligent healthcare based RPM of ADL in elderly patients. The overall goals of experiments will be to initially establish accuracy of beacons in simple, predictable environments and expand their monitoring capabilities in complex environments experienced in home healthcare.

3.1 Experiment Conditions and Metrics

Experiments take place within an appartment building with a variety of rooms including a bathroom, bedroom, living room, kitchen and office. These enviroments are mapped to potential conditions sought by ADL standards, described in table 1, toilet signfiying likely bathing etc. Accuracy between beacon and receiver is measured by placing both inside a room with no barriers to radio signal, the actual distance is then measured across a horizontal plane between the two. Physical distance is measured between the BLE beacon and the receiver using measuring tape while the reported distance is determined using beacon RSSI transmitted to the receiver. The forementioned metrics used in experiments are displayed in table 2.

Table 2: Metrics used in experiments.

Metric	Description
Received Signal Strength (RSSI)	Measurement of the power present in a received radio signal.
TX Power	TX is the power transmitted in decibels per milliwatt (dBm) (Garg, K. and Pandey, 2016)
Advertisement Interval (MS)	The time interval between packets has broadcasted measured in micro seconds (MS)
Major/Minor	The UUID parameters of beacon identifiers.
Distance Reported	Distance in metres calculated from RSSI and TX Power
Actual Distance	Physical measured distance in metres from beacon and receiver

3.2 Experiment Stages

Experiments take place in stages as future work will depend on initial experiments to obtain acceptable degrees of accuracy across multiple use cases such as using a variety of power outputs, identification of rooms and use of objects by occupant wearing a receiver. Experiments are performed within an empty room in the test apartment with no barriers between the beacon and receiver.

3.2.1 Proximity Accuracy

Proximity accuracy experiments seek to establish how accurate BLE beacons are when estimating the distance between the beacon and the receiver when within its radius of advertisement. Several factors could affect this including TX Power output, advertisement interval and physical barriers to radio waves. Accuracy tests first measure RSSI and thus distance over distances between sender and receiver such as .1 metres, .5 metres and 1 metre etc. Further tests then moved beacons either closer or further away and measured accuracy of distance interpretation. TX Power outputs were also altered to access impact of proximity accuracy.

3.2.2 Multiple Room Patterns

Proximity devices placed in multiple rooms of the test apartment builds on what is understood from the previous experiment. With established accuracy, obtained by altering TX Power and advertisement interval, within one room the beacons are then placed in multiple rooms while a receiver is placed in one room. RSSI and distance reported is measured between all beacons and the receiver. The receiver will, depending on the test, remain stationary in one room or be placed in different rooms with the movement event between rooms captured in data.

3.2.3 Objects of Interest

Further experiments will test beacons placed on objects with the intention to understand how frequent, if at all an occupant manipulates an item such as a microwave, kettle or water bottle. Experiments will include time set manipulations of these objects by a participant wearing a receiver and random manipulations of OOI. The goal is to witness interactions between patients and objects of importance to their ADL.

3.2.4 Data Analysis Experiments

With proximity, multiple room and object manipulation accuracy established experiments focus on incorporating ADL into an automated algorithm which recognises relevant ADL patterns in activity monitored data. Experiments to determine accuracy of recognitions will take place with a participant performing tasks within the test environment and the data examined to pair the interaction with proximity variables.

3.2.5 Participant Experiments

With established data analysing algorithms, participants experiments will explore activity monitoring capabilities across a variety of circumstances including using different testing environments such as houses, number of beacons, participants on schedules and experiments without participants schedules to follow. These experiments demonstrate the effectiveness of BLE beacons for both accurately capturing interactions relevant to ADL analysis within intelligent healthcare and the use in the RPM of NCDs as an aide to care givers.

4 RESULTS & DISCUSSION

Results described in this section cover proximity accuracy and multiple room pattern experiment subsections. Tests for accuracy follow a standard of multiple distances measured vs actual with multiple power outputs. Multiple room tests refer to average distance reported to determine which of the multiple rooms the receiver is currently in, during all experiments the receiver is moved to different locations and new actual distances recorded.

4.1 Proximity Accuracy: Calibration

Table 3 shows the accuracy of reported distance vs actual distance when both TX Power and advertisement interval are altered. For alternating tests, the corresponding value is set to maximum, for TX Power this is -4dbm and for interval it is 100ms. Each test displayed is an average of over 1000 captures using BLE beacons and a phone application acting as the receiver.

Table 3: TX Power & Interval Effect on Accuracy.

TX Power and Advertisement Interval	Reported Distance vs Actual Distance Accuracy (AVG, 1000 Captures)
-4dbm (Interval 100ms)	77% Accurate
-10dbm (Interval 100ms)	73% Accurate
-20dbm (Interval 100ms)	70% Accurate
-40dbm (Interval 100ms)	69% Accurate
200ms (TX -4dbm)	77% Accurate
500ms (TX -4dbm)	76% Accurate
800ms (TX -4dbm)	74% Accurate
1000ms (TX -4dbm)	74% Accurate

Perhaps not surprisingly, using the highest power output of -4dbm achieved the highest accurate value between distance reported and actual measured distance, with the same being true of advertisement interval although the affect was not as noticeable possibly due to the fact captured results are aggregated. Illustrating this result visually, figure 3 shows the results from a proximity accuracy experiment with 1200 captures and maximum values for both advertisement interval and TX Power. During the experiment the beacon maintained a stationary position while the receiver moved closer across a horizontal surface. The movement intervals were 2.5M to 2M to 1M with 15 minutes of captures recorded in each state. Figure 3 illustrates an erratic line which represents beacon reported distance and a solid line which represents actual distance from beacon to receiver.

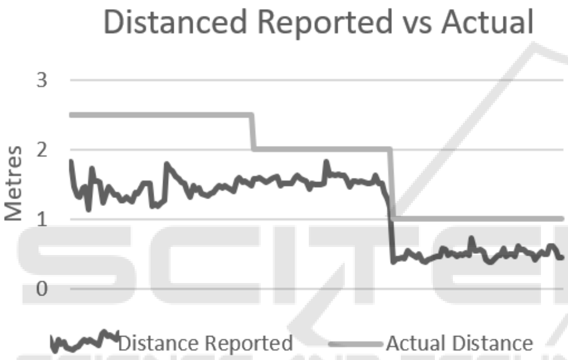

Figure 3: Beacon Accuracy: Actual vs Reported Distance.

As the receiver moves closer during predetermined distance changes it is clear the beacon records this interaction with signal strength increasing following for a smaller reported distance which becomes more accurate the closer the receiver gets to the beacon with an overall accuracy of 78.1% which is in line with previous experiments using this TX Power and advertisement interval. All further tests would use these values

4.2 Multiple Room: Distinguishing Values

The goal of the multiple room testing phase was essentially to determine which room an occupant was both in and moving towards with multiple beacon outputs being intercepted by one receiver.

Distinguishing values would be the highest relative RSSI when compared to competing beacon signal, the factor of this accuracy would need to be determined.

Table 4: Multiple Room: Stationary Receiver Test.

Beacon Location	Distance from Office	Distance from LR	Distance from Bedroom
Office (Reported)	1.18m	3.32m	3.14
Office (Actual)	1.3m	4.12m	3.2m

Table 4 shows a signal experiment in which the receiver was placed in the office of the experiment environment. Without moving from its location over 30 minutes of captures recorded its location as being nearest to the office beacon, while being almost equally far from the bedroom as from the sitting room which is an accurate result. This test also recorded good accuracy between actual and reported distances through barriers such as walls. Further to multiple room experiments examined in non-stationary tests were also carried out which involved the same beacon layout as the experiment detailed in table 4. Each predetermined movement event occurred within 15 minutes and one 30-minute interval with the receiver being moved between rooms while recording showing a pattern of motion between areas as RSSI fluctuated between beacons.

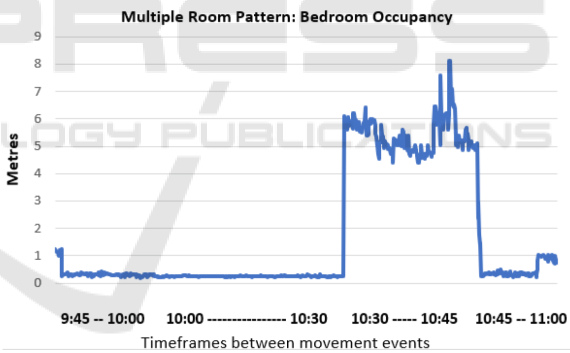

Figure 4: Beacon Accuracy: Bedroom Beacon.

The results can be seen in figure 4,5 and 6 while location and times can be seen in table 5. Figures 4,5 and 6 show the data captured by the BLE bedroom beacon between the times of 9:45 and 11:00.

Table 5: Multiple Room: Receiver Movement Between Rooms.

Timeframe	Receiver Location
9:45 - 10:00	Office
10:00– 10:30	Bedroom
10:30– 10:45	Sitting Room
10:45– 11:00	Bedroom

The beacon estimates proximity during early timeframes as the beacon is in the adjacent room, the office. From 10:00 to 10:30 the bedroom beacon reports very close proximity as now the receiver is physically in the bedroom. From 10:30 to 10:45 the bedroom beacon reports a now significant gap between itself and the receiver of up to 8 metres which is accurate as the receiver as moved some distance and between two walls to the sitting room.

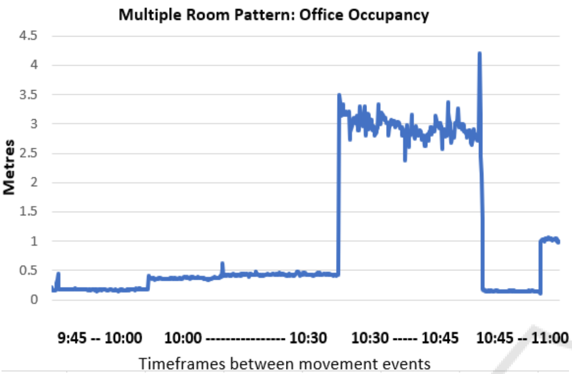

Figure 5: Beacon Accuracy: Office Beacon.

The pattern continues as the receiver is moved from the bedroom to the sitting room, the office beacon just has a wall between and it and the receiver and this is visible in the data. Figure 5 illustrates the data captured from the office beacon. The initial office timeframe reports proximity accurately between 9:45 and 10:00, this is slightly increased in line with the movement event from office to bedroom. And finally figure 6 shows this multiple room experiment from the point of view of the sitting room beacon. During the early periods between 9:45 and 10:30 there is significant distances from this beacon between the closer office and bedroom beacons. This distance reported is almost inversely proportional to distance gaps observed from the office and bedroom perspectives. With a consistent accuracy observed between 10:30 and 10:45 when the receiver is placed in the beacons near radius emission.

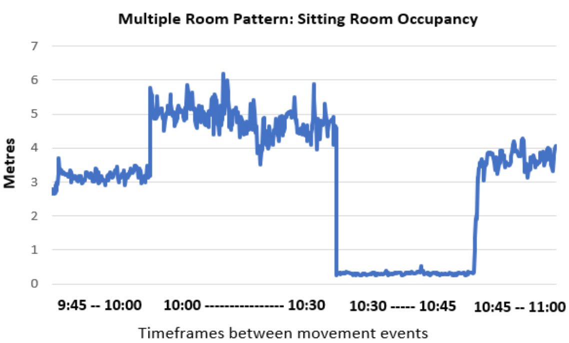

Figure 6: Beacon Accuracy: Sitting Room Beacon.

4.3 Discussion

The experiments conducted within the first two phases of the planned efficacy process indicates a reasonable, predictive degree of accuracy can be obtained by BLE beacons used as part of an IPS for activity monitoring. With consistent results of RSSI used for distance calculations, multiple room beacon experiments have begun to show data which can be interpreted to ascertain the movement events of a receiver device. Patient patterns are expected to be more erratic and unpredictable, and hence further experiments within these phases will be conducted to continue building upon the efficacy of these devices in these individual scenarios before experiments using occupants with intentionally erratic schedules.

Following this phase described in figure 6, focus will turn to experiments to develop consistent reliable ADL based triggers within data analysis and overall answering the question as to the role of BLE in intelligent healthcare monitoring.

4.4 Conclusions

National healthcare services cannot continue to coupe under the strain the aging population and the rise of NCDs have placed upon them. This leaves technology based 'intelligent' forms of healthcare as one of the few remaining realistic solutions (Campling, 2014). As discussed, activity monitoring has a significant role in the management, treatment, diagnosis and in some cases prevention of NCDs which the elderly suffers from the most and which cause not only the largest strain on the healthcare system but also account for most deaths in the UK. Research into intelligent healthcare solutions for this problem is however limited by the technology itself. Although sensors used in RPM have proven to be successful (Nakamura et al, 2013), activity and lifestyle monitoring has become an issue while using occupancy technologies such as PIR sensors, door sensors and chair sensors. There is also a large gap in the ability to provide monitoring for elderly who suffer from dehydration and malnourishment, a significant attributor to NCDs and death in that age group (Lavizzo-Mourey, Johnson and Stolley, 1988).

This paper has considered, BLE Beacons in use as a part of an IPS which utilises successful RPM techniques to potentially fill the gap left by inaccurate devices and lack of ability to approximate use of objects which would indicate a patient keeping themselves nourished and dehydrated. Currently this is completed by a community care nurse, as profession rapidly disappearing (Royal College of

Nursing, 2012) Results so far indicate a high degree of approximate accuracy with limited obstacles using a single BLE beacon. Motion and movement of a receiver within range of a beacon is easily identifiable within captured data as BLE has demonstrated the ability to output a high advertisement interval without compromising on battery, a significant barrier to other devices (Samarrai and Greene, 2011).

5 FUTURE WORK

Additional experiment phases such as the multiple room experiments have shown that using multiple BLE beacons with one receiver, it is possible to accurately determine the room the receiver is currently occupying. Further tests showed the pattern of movement and the potential path this receiver took while moving between BLE beacon ranges accurately. Additional phases of experiments need to take place however, the most significant of which involves incorporating pattern reading algorithms using ADL to read and flag ADL condition degeneration over a period. Although the outcomes of using BLE as an IPS are speculated to be beneficial to care givers both informal and formal the extent of BLE application scope for home healthcare may not be predicted without additional experimental phases using OOI and data analysis algorithms.

REFERENCES

Allard, M., Husky, M., Catheline, G., Pelletier, A., Dilharreguy, B., Amieva, H., Pérès, K., Foubert-Samier, A., Dartigues, J.-F. and Swendsen, J. (2014) *'Mobile technologies in the early detection of cognitive decline'*, PLoS ONE, 9(12), p. e112197

Armstrong, G.L. (1999) *'Trends in infectious disease mortality in the United States during the 20th century'*, JAMA, 281(1), p. 61. doi: 10.1001/jama.281.1.61.

Barlow, J., Singh, D., Bayer, S. and Curry, R. (2007) *'A systematic review of the benefits of home telecare for frail elderly people and those with long-term conditions'*, Journal of Telemedicine and Telecare, 13(4), pp. 172–179.

Campling, P. (2014). *Intelligent Kindness: professional healthcare and the future of the UK NHS*. European Journal for Person Centered Healthcare, 2(2), p.235.

CarersUK (2015) Https://www.Carersuk.Org/for-professionals/policy/policy-library/facts-about-carers-2015).

Chiauzzi, E., Rodarte, C. and DasMahapatra, P. (2015). *Patient-centered activity monitoring in the self-management of chronic health conditions*. BMC Medicine, 13(1).

Dye, C. (2014) *'After 2015: Infectious diseases in a new era of health and development'*, 369(1645).

Feil, C. (2016). *Indoor Positioning: Opportunities and implementation strategies of Bluetooth Low Energy*. *GI_Forum*, 1, pp.94-105.

Garg, A., K., R. and Pandey, M. (2016). *Review of Energy Harvesting Techniques for Wireless Sensor Nodes*. Communications on Applied Electronics, 5(7), pp.1-4.

Goats, G. (1988). *Appropriate Use of the Inverse Square Law*. Physiotherapy, 74(1), p.8.

Katz, S. (1983). *Assessing Self-maintenance: Activities of Daily Living, Mobility, and Instrumental Activities of Daily Living*. Journal of the American Geriatrics Society, 31(12), pp.721-727.

Kim, D., Kim, S., Choi, D. and Jin, S. (2015). *Accurate Indoor Proximity Zone Detection Based on Time Window and Frequency with Bluetooth Low Energy*. Procedia Computer Science, 56, pp.88-95.

Kyoung Nam Ha Kyung Chang Lee, Suk Lee (2006). *Development of PIR Sensor Based Indoor Location Detection System for Smart Home*. Journal of Control, Automation and Systems Engineering, 12(9), pp.905-911.

Lavizzo-Mourey, R., Johnson, J. and Stolley, P. (1988). *Risk Factors for Dehydration Among Elderly Nursing Home Residents*. Journal of the American Geriatrics Society, 36(3), pp.213-218.

Lavizzo-Mourey, R., Johnson, J. and Stolley, P. (1988). *Risk Factors for Dehydration Among Elderly Nursing Home Residents*. Journal of the American Geriatrics Society, 36(3), pp.213-218.

Office for National Statistics (2015). *Population Estimates for UK, England and Wales, Scotland and Northern Ireland*, Mid-2014 - ONS. [online] Available at: http://www.ons.gov.uk/ons/rel/pop-estimate/populationestimates-for-uk--england-and-wales--scotland-and-northern-ireland/mid-2014/index.html [Accessed 25 January. 2017].

Office for National Statistics (2016) *Deaths registered in England and wales: 2015*. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/bulletins/deathsregisteredinenglandandwalesseriesdr/2015 (Accessed: 08 February 2017).

Royal College of Nursing (2012) *The Community Nursing Workforce in England*, Available at: https://my.rcn.org.uk/__data/assets/pdf_file/0003/450525/09.12_The_Community_Nursing_Workforce_in_England.pdf (Accessed: November 2016).

Stowe, S., & Harding, S. (2010). Telecare, telehealth and telemedicine. European Geriatric Medicine, 1(3), 193–197. http://doi.org/10.1016/j.eurger.2010.04.002

Samarrai, T. and Greene, C. (2011). *Clinician Acceptance of Computerized Alerts for Public Health Surveillance*. Journal of Health & Medical Informatics, 7(4).

Nakamura, N., Koga, T., & Iseki, H. (2013). *A meta-analysis of remote patient monitoring for chronic heart failure patients*. Journal of Telemedicine and Telecare, 20(1), 11–17. doi:10.1177/1357633x13517352

Nangalia, V., Prytherch, D. and Smith, G. (2010). *Health technology assessment review: Remote monitoring of vital signs - current status and future challenges*. Critical Care, 14(5), p.233

Vegesna, A., Tran, M., Angelaccio, M. and Arcona, S. (2017) *'Remote patient monitoring via non-invasive digital technologies: A systematic review', Telemedicine and e-Health*, 23(1), pp. 3–17. doi: 10.1089/tmj.2016.0051. WHO (2014) Global health workforce shortage to reach 12.9 million in coming decades. Available at: http://www.who.int/media centre/news/releases/2013/health-workforce-shortage/en/ (Accessed: 05 February 2017).

WHO (2012) *Deaths from NCDs*. Available at: http://www.who.int/gho/ncd/mortality_morbidity/ncd_total/en/ (Accessed: 05 February 2017).

Zhang, D., Wang, W. and Lv, L. (2017). *Research on Algorithm of Indoor Positioning System Based on Low Energy Bluetooth 4.0*. ITM Web of Conferences, 11, p.03007.

Zhao, X., Xiao, Z., Markham, A., Trigoni, N. and Ren, Y. (2014). *Does BTLE measure up against WiFi? A comparison of indoor location performance*. In: European Wireless 2014. [online] VDE. Available at: http://ieeexplore.ieee.org/abstract/document/6843088/ [Accessed 13 Jul. 2017].